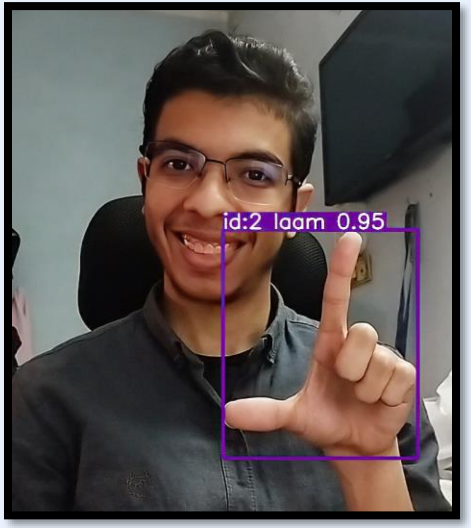
Arabic Sign Language Real-Time Recognition



(Using YOLOv8 Object Detection)

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01

Arabic Sign Language (ASL)

Arabic Sign Language

Arabic Sign Language (ASL)

A visual-gestural language used by deaf and hard of hearing communities primarily in our Arabian world. Just like spoken languages, ASL has its own grammar, syntax, and vocabulary. It involves the use of handshapes, movements to convey meaning and communicate ideas. In recent years, there has been increased attention to developing technologies that facilitate the recognition and translation of ASL gestures, aiming to enhance accessibility and communication for individuals who use sign language.

Lam - ل

Arabic Sign Language

Arabic Letters resembled by sign language

YOLO Architecture

YOLO (You Only Look Once)

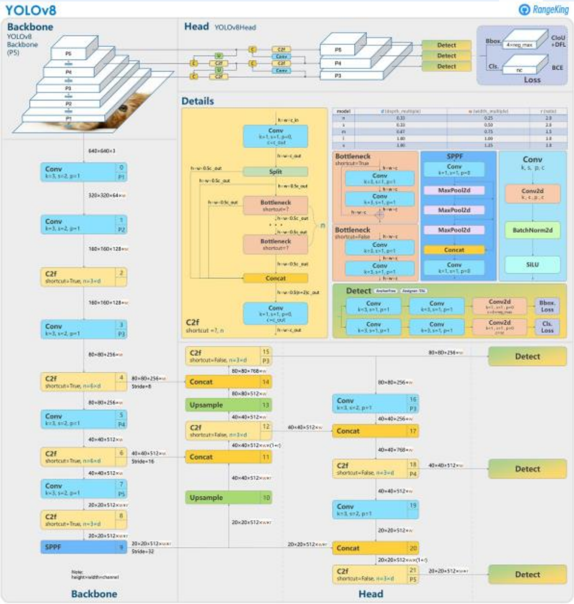
YOLO is known as a SOTA (State-Of-The-Art) approach and architecture that’s widely used in object detection along with many other tasks. We used the YOLOv8 model

YOLO consists of many parts, mainly:

1. Backbone: The backbone is the foundational part of the architecture responsible for extracting meaningful features from the input image, typically made of Convolutional Neural Networks (CNNs) such as DarkNet in YOLO.

2. Neck: The neck sits between the backbone and the head. It performs additional feature fusion or transformation to enhance the representations learned by the backbone.

3. Head: the head consists of convolutional layers that predict bounding boxes, objectness scores (indicating the presence of an object), and class probabilities for each grid cell in the feature map generated by the backbone and neck.



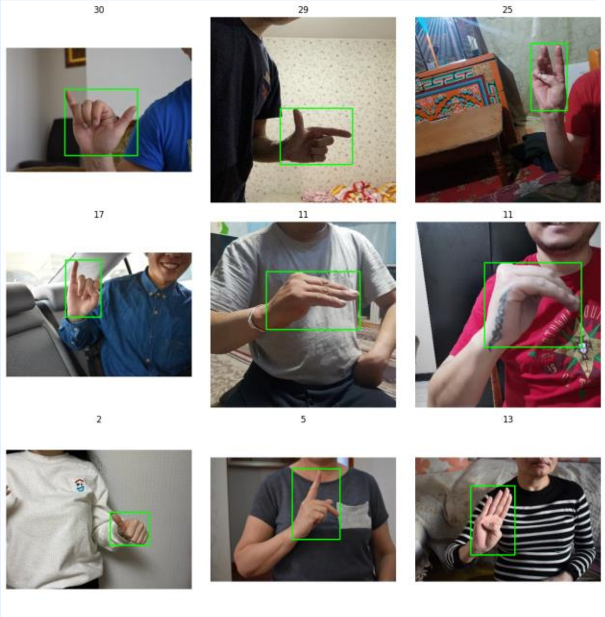
YOLOv8Architecture

Dataset

Arabic Sign Language Dataset 2022

https://www.kaggle.com/datasets/ammarsayedtaha/arabic-sign-language-dataset-2022

The Dataset consists of 14202 images covering the 32 Arabic Signs of letters by hands made by 50 different persons, 9955 samples are used for training, while the rest 4247 samples are used for evaluating the model for generalization and performance on unseen data.



9 Plotted samples with their corresponding boundary box and label

Model Fine-Tuning

Hyper-Parameters:

Epochs: 100

Image Size: 256

batch Size: 128

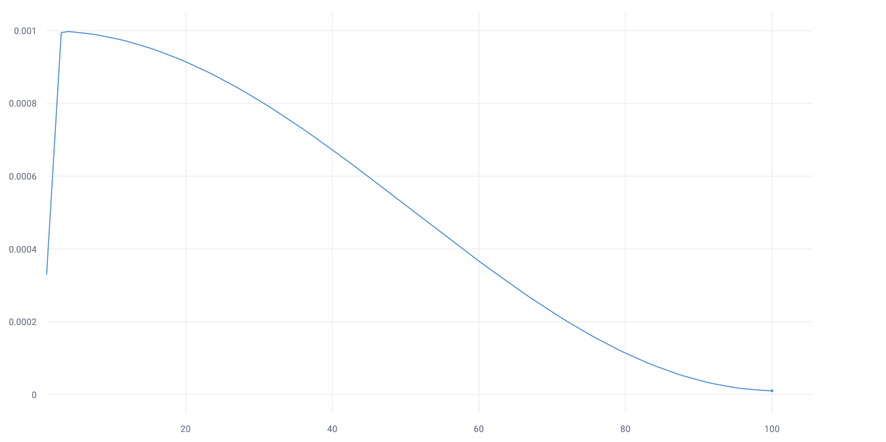
Optimizer: Adam

Initial Learning Rate: 0.001

momentum (beta for Adam): 0.9

Learning Rate Scheduler: Cosine Scheduler

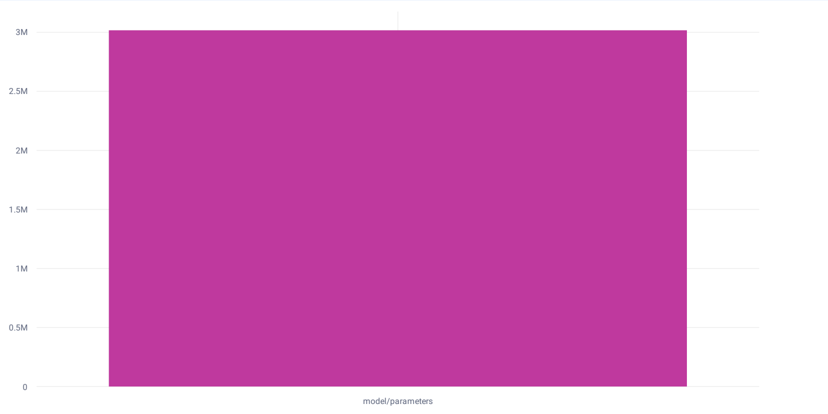
Random Seed: 42



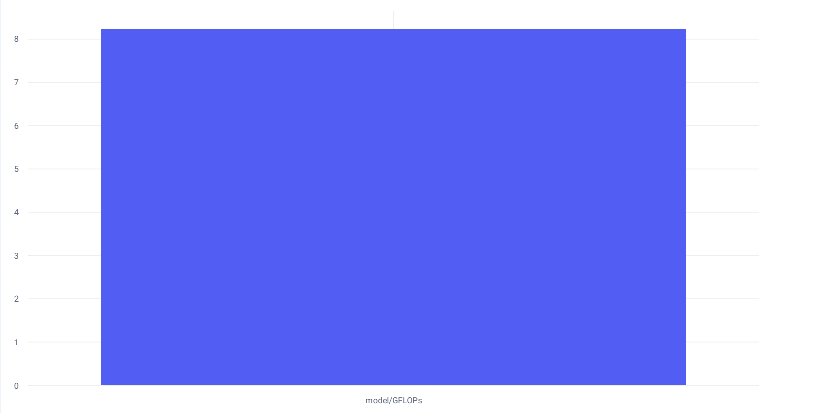
Cosine Learning Rate Scheduler Effect

Model Fine-Tuning

Model's Parameters:



3.017 Million Parameters



8.227 GFlOPs

Metrics & Results

System Specs:

GPU: Nvidia RTX 3060 12GB VRAM

CPU: Intel I5-10400F 2.90 GHz

RAM : 16GB

OS: Windows 11 Pro

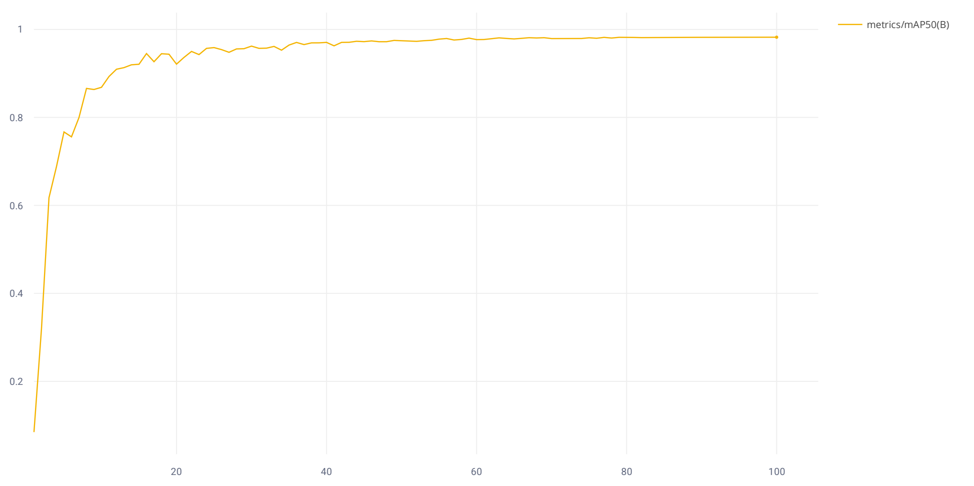
Frameworks:

- Visual Studio Code
- Python
- Ultralytics (YOLO)
- OpenCV

Metrics & Results

mAP50

measures the average precision of correctly identifying background regions or areas with no objects of interest in the image. It evaluates how well the model can distinguish between objects and background regions.

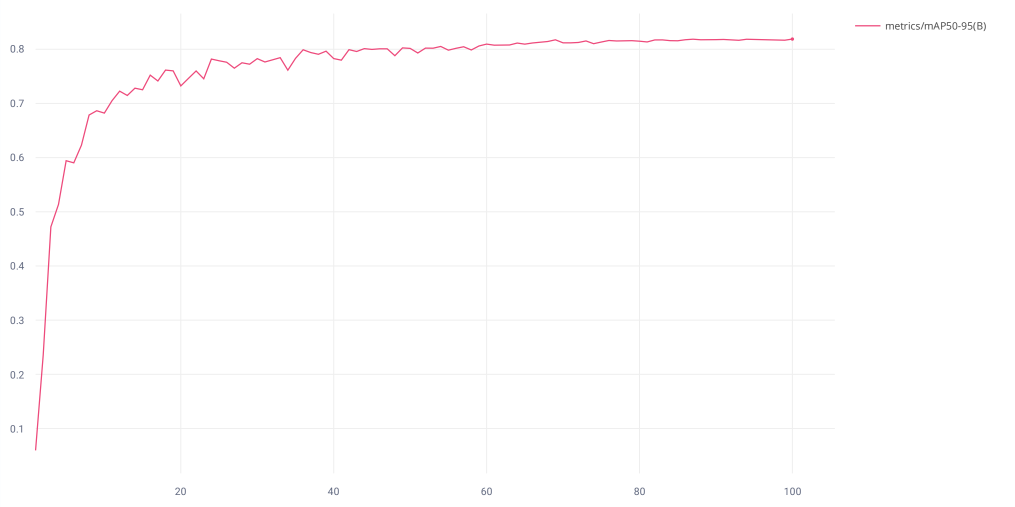


mAP50 Through the epochs
98.24% at Epoch 100

Metrics & Results

mAP50-95

calculates the average precision across a range of IoU thresholds (from 0.5 to 0.95) for background regions. It provides a broader assessment of the model's performance across various levels of overlap between predicted and ground truth bounding boxes.

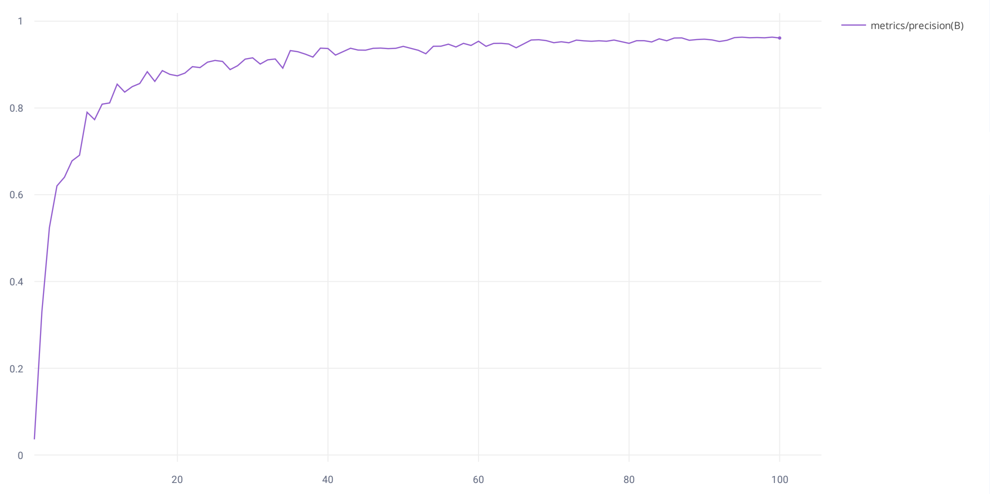


mAP50-95 Through the epochs
81.89% at Epoch 100

Metrics & Results

Precision

measures the proportion of correctly predicted background regions out of all regions classified as background by the model. It indicates the model's ability to avoid falsely identifying objects in background regions.

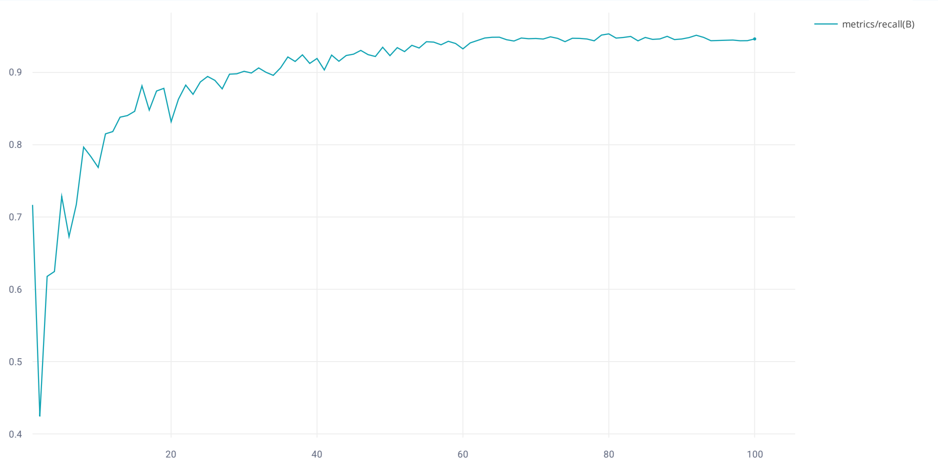


Precision Through the epochs
96.14% at Epoch 100

Metrics & Results

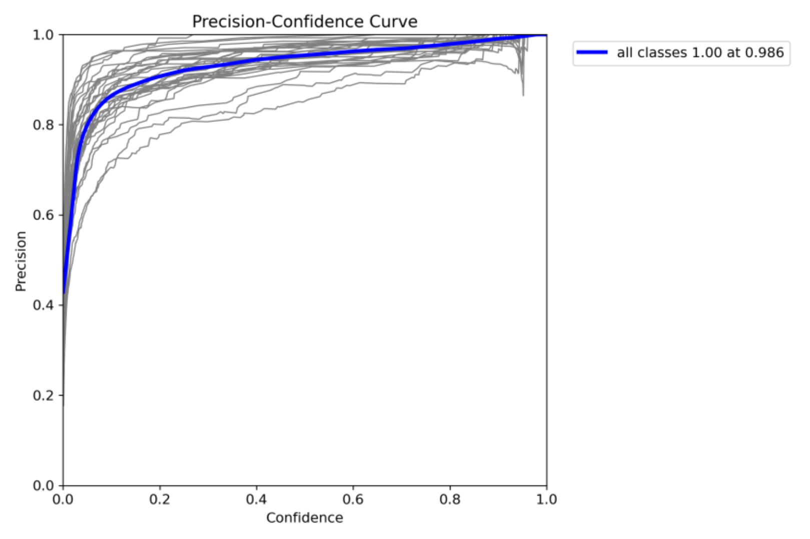
Recall

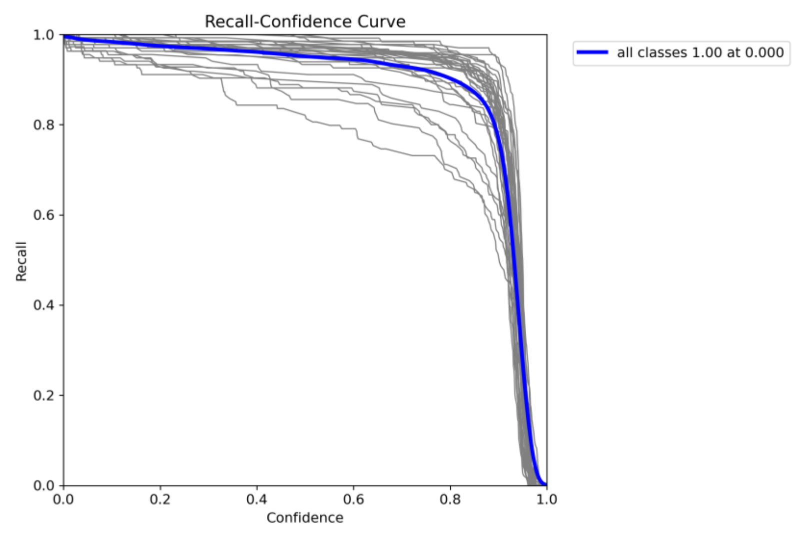
calculates the proportion of correctly identified background regions out of all actual background regions in the image. It assesses the model's ability to detect all background regions, including those that might be challenging to differentiate from objects.



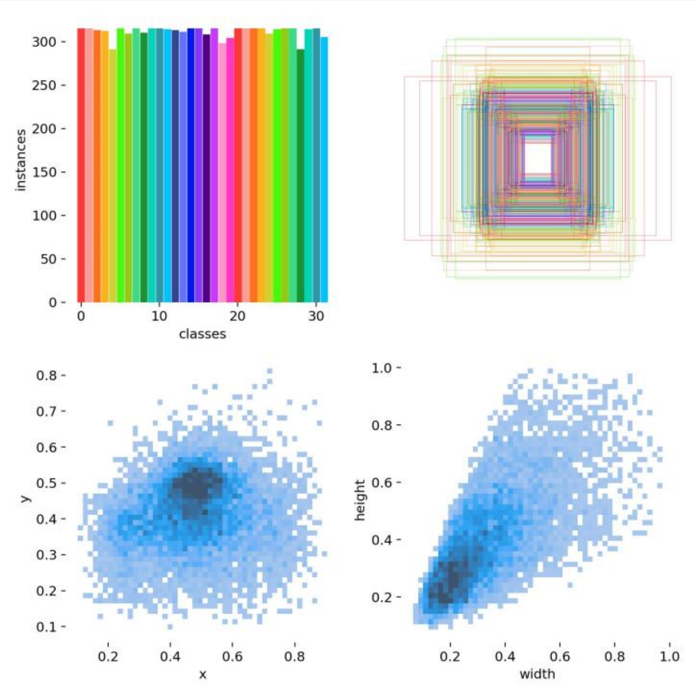
Precision Through the epochs
96.14% at Epoch 100

Metrics & Results

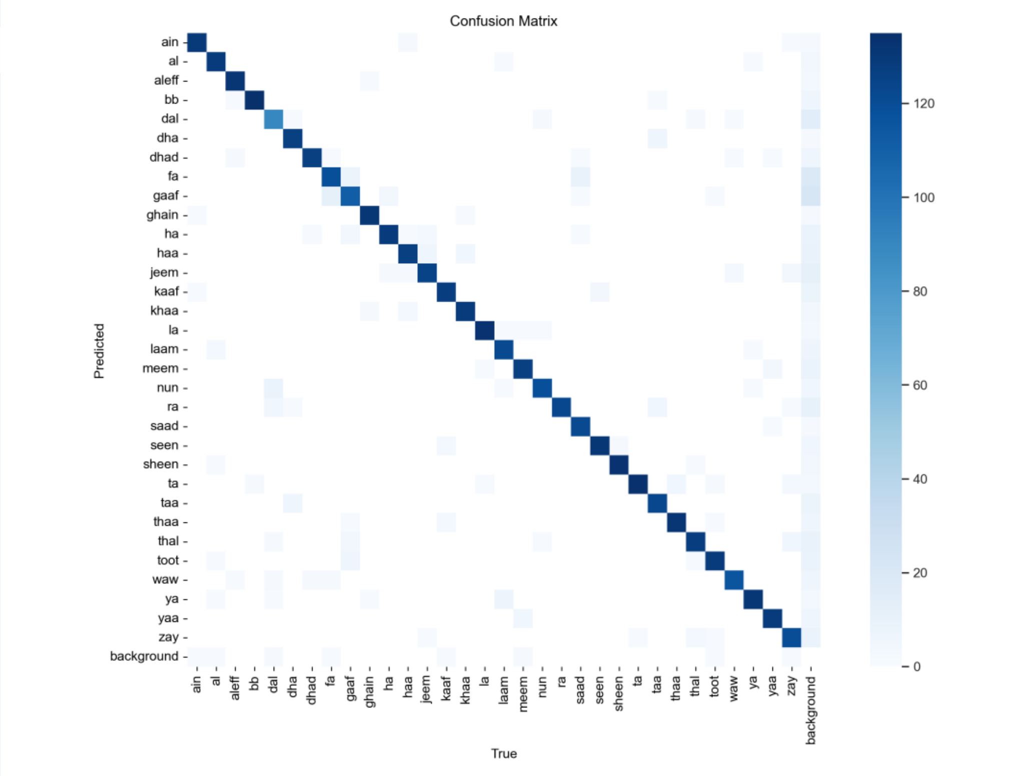


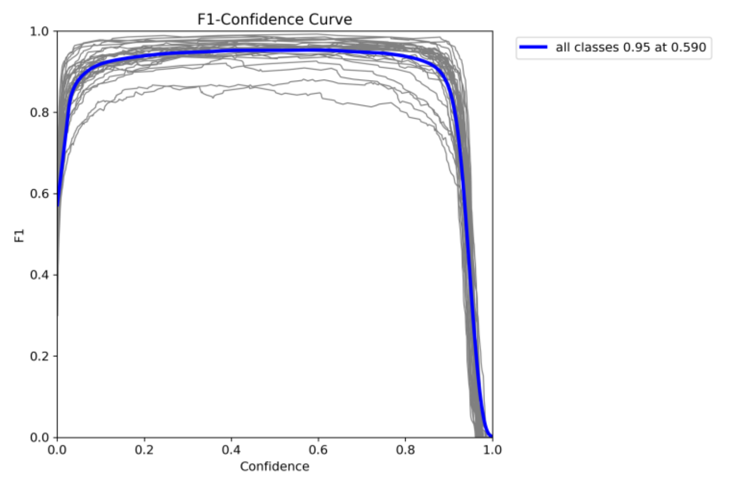


Metrics & Results

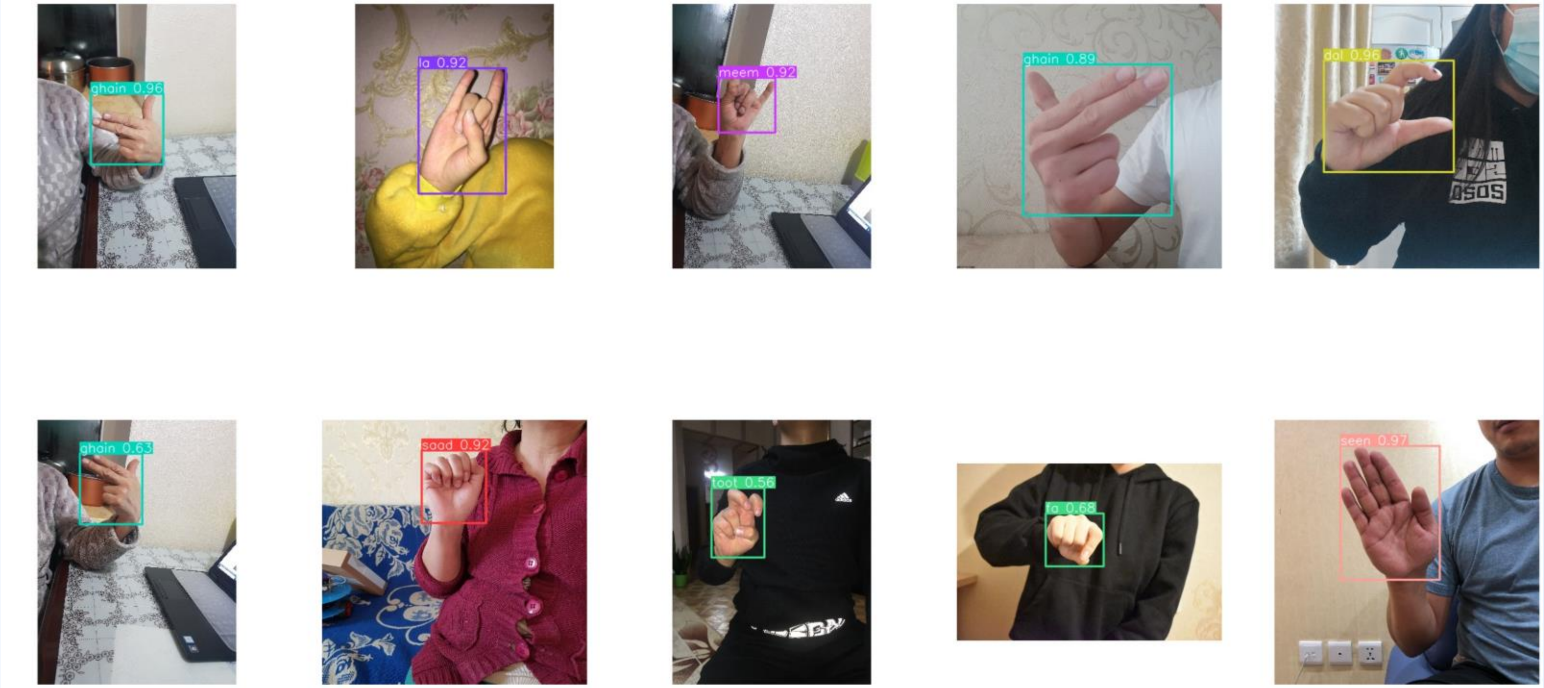


Metrics & Results



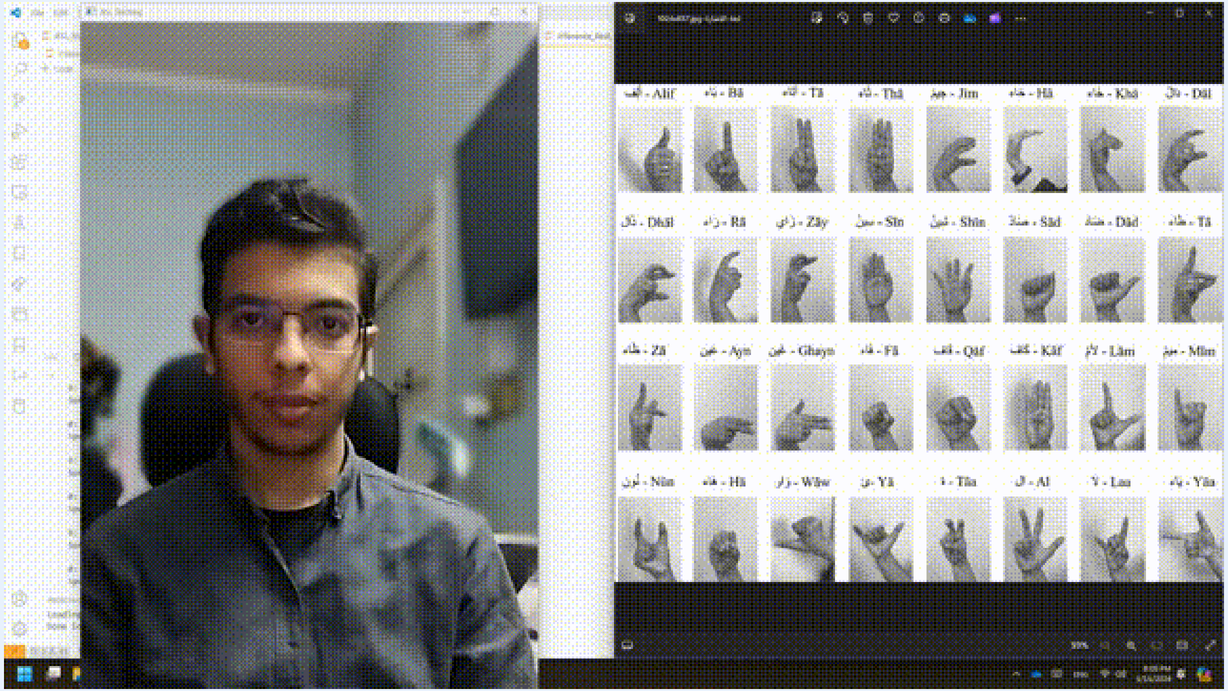


Metrics & Results



Inference of the model on some images of the Validation set

Metrics & Results



A Real-Time Inference of the model

Code Snippets

```python
from ultralytics import YOLO
import os
import numpy as np
import matplotlib.pyplot as plt
import cv2
import random

import comet_ml
comet_ml.init()
```

Imports

Code Snippets

```python
def read_labels(label_path):
    with open(label_path, 'r') as file:
        lines = file.readlines()
        labels = [line.strip().split() for line in lines]
    return labels

def draw_boxes(image, labels):
    for label in labels:
        class_id = int(label[0])
        x, y, w, h = map(float, label[1:])
        image_height, image_width, _ = image.shape
        x1 = int((x - w / 2) * image_width)
        y1 = int((y - h / 2) * image_height)
        x2 = int((x + w / 2) * image_width)
        y2 = int((y + h / 2) * image_height)
        color = (0, 255, 0)  # Green
        cv2.rectangle(image, (x1, y1), (x2, y2), color, 2)
    return image

data_dir = 'train'

image_files = [file for file in os.listdir(os.path.join(data_dir, 'images')) if file.endswith('.jpg')]

random.shuffle(image_files)

fig, axes = plt.subplots(3, 3, figsize=(12, 12))
for ax, image_file in zip(axes.ravel(), image_files[:9]):
    image_path = os.path.join(data_dir, 'images', image_file)
    label_path = os.path.join(data_dir, 'labels', os.path.splitext(image_file)[0] + '.txt')

    # Read image
    image = cv2.imread(image_path)
    image_rgb = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

    # Read labels
    labels = read_labels(label_path)

    # Draw bounding boxes on the image
    image_with_boxes = draw_boxes(image_rgb, labels)

    # Display image with bounding boxes and set the labels as titles
    ax.imshow(image_with_boxes)
    ax.set_title(str(labels[0][0]))
    ax.axis('off')

plt.tight_layout()
plt.show()
```

Visualizing Training Samples

Code Snippets

```python
model = YOLO('yolov8n.yaml')
model = YOLO('yolov8n.pt')
model = YOLO('yolov8n.yaml').load('yolov8n.pt')
```

```python
history = model.train(data='sign.yaml', epochs=100, imgsz=256,
                      patience = 100, batch = 128,
                      project ="ASL", optimizer = 'Adam', momentum = 0.9,
                      cos_lr=True ,seed = 42, plots = True , close_mosaic = 0, lr0 = 0.001)
```

Model Training

Code Snippets

```python
# Loading Model
trained_model = YOLO('ASL.pt')
```

```python
test_images_dir = 'valid/images'
test_images = [os.path.join(test_images_dir, image) for image in os.listdir(test_images_dir)]

test_samples = np.random.choice(test_images, 10, replace=False)

print(test_samples)
```

Loading Model and Making Predictions

Code Snippets

```
results = trained_model([test_samples[0], test_samples[1], test_samples[2], test_samples[3], test_samples[4], test_samples[5], test_samples[6], test_samples[7], test_samples[8], test_samples[9]])

results_dir = "results_tries"
if not os.path.exists(results_dir):
    os.makedirs(results_dir)

i = 0
for result in results:
    boxes = result.boxes
    masks = result.masks
    keypoints = result.keypoints
    probs = result.probs

    # Save image
    filename = os.path.join(results_dir, f"result_{i}.jpg")
    result.save(filename=filename)
    # result.show() # Uncomment to display image
    i+=1
```

Loading Model and Making Predictions

Code Snippets

```python
directory = "results_tries"

images = []
for filename in os.listdir(directory):
    if filename.endswith(".jpg"):
        img = plt.imread(os.path.join(directory, filename))
        images.append(img)

fig, axs = plt.subplots(2, 5, figsize=(50, 25))
for i in range(10):
    axs[i//5, i%5].imshow(images[i])
    axs[i//5, i%5].axis('off')

plt.show()
```

Loading Model and Making Predictions

Code Snippets

```python
import cv2
from ultralytics import YOLO

# Load the model
model = YOLO('ASL.pt')

# Open the camera
cap = cv2.VideoCapture(0)

# Setting width and height of the video
cap.set(cv2.CAP_PROP_FRAME_WIDTH, 1920)
cap.set(cv2.CAP_PROP_FRAME_HEIGHT, 1080)


while cap.isOpened():

    success, frame = cap.read()

    if success:

        results = model.track(frame, persist=True)


        annotated_frame = results[0].plot()

        cv2.imshow("ASL Tracking", annotated_frame)

        # Break the loop if 'q' is pressed
        if cv2.waitKey(1) & 0xFF == ord("q"):
            break
    else:
        # Break the loop if
        break

cap.release()
cv2.destroyAllWindows()

```

Real-Time Inference

Thank You!